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Investigations on the identification of pests in horticultural crops under greenhouse conditions

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Abstract: The early detection of pests in plants and crops is essential for the production of good quality food. Computer vision techniques can be applied for the early detection of pests and which can minimise the pesticides used on the plants. Among many pests, white flies, mites, aphids and thrips are the most hazardous pests that affect the leaves. This paper presents an automated approach for the detection of different types of pests from leaf images of plants. The images of the plant leaves were acquired using a digital camera. Image pre-processing techniques, such as noise removal, filtering and contrast enhancement, are used for improving the quality of the images. Then, the *k*-means clustering method and global thresholding were used for segmenting the pests from the infected leaves. Textural features are extracted from those segmented images by statistical feature extraction methods. Artificial Neural Network (ANN) and Binary Support Vector Machine (SVM) classifiers were used to classify the unaffected leaf images from the pest affected leaf images and a multi-SVM classifier was used to identify the different types of pests.

Keywords: pest identification, image processing, artificial neural network, support vector machine, green house

Agriculture plays an important role in the economy of developing countries across the world. The presence of pests on crops has restricted the quality of agricultural produce. If the presence of pests on crops is not checked properly then the quantity of food production will be reduced, as a result there will be an increase in poverty and food insecurity. This can affect any nation's economy that depends on agriculture. The most common pests that affect plants are aphids, white flies, thrips and mites. Therefore, it is important to detect these pests at all stages of their lifecycle.

One way to control pest infections is by using pesticides. Pesticides will suppress a particular pest species. Pesticides are detrimental for the environment and produce considerable damage to ecosystems. The excessive use of pesticides will pollute the air, water, and soil. It also decreases the general biodiversity in the soil. Hence, the early detection of pests or the initial presence of pests is a key-point for crop management. In greenhouses, the staff periodically observe plants and search for pests. This manual method is very time consuming.

The monitoring of a pest infestation relies on manpower; however automatic monitoring has been advancing in order to minimise human efforts and errors. The study extends the implementation of different image processing techniques (Gonzalez, Woods 1992; Johnny 2014; Awcock 2016) to detect and extract insect pests by establishing an automated detection and extraction system for estimating pest densities in paddy fields (Zhu 2010). The disease detection of cercosporin leaf spot in sugar beets by robust template matching is a novel approach based on

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orientation code matching for the robust and continuous observations of disease development in sugar beet plants (Zhou 2014). (Faithpraise et al. 2013) demonstrate the combination of the k-means clustering algorithm and the correspondence filter to achieve pest detection and recognition. The detection of the dataset is achieved by partitioning the data space into Voronoi cells, which then tends to find clusters of comparable spatial extents, thereby separating the pests from the background.

The production of agricultural cultivation in greenhouses requires of large quantities of pesticides for pest control. Pesticide applications are a major component of plant production costs in greenhouse, and excess applications have a great negative impact on the environment (Li et al. 2009). In a 3-D vision system of a tomato production robot, a 3-D vision sensor was made and attached at the end of the manipulator. The sensor emitted red and infrared laser beams to scan the object. Image recognition experiments for the fruit harvesting work and the plant training work were carried out (Gotou et al. 2003). In order to reduce production costs, a harvesting robot system for strawberries on an elevated-trough culture was designed. It was supposed to serve for sightseeing agriculture and technological education (Kondo 2000). An optimal threshold was selected by the discriminant criterion, so as the maximise the separability of the resultant classes in the grey levels. The procedure is very simple, utilising only the zeroth- and first-order cumulative moments of the grey-level histogram (Otsu 1979).

Machine vision-based systems were developed for monitoring various crops (Jiminez et. al 2000; Too et. al 2019). According to the multifractal dimension, the candidate blobs of whiteflies were initially defined from the leaf image. The regional minima were utilised for the feature extraction of the candidate whitefly image area (Li et al. 2015). An insect imaging system to automate the rice light-trap pest identification and the counting of rice light-trap pests are important to monitor the rice pest population dynamics and make pest forecasts. The manual identification and counting of rice light-trap pests is time-consuming, and leads to fatigue and an increase in the error rate (Quing et al. 2012). Artificial neural networks (Li et. al. 2020; Rahman et al. 2020) and a support vector machine (Platt 1999; Patil et. al. 2012) can be used as pattern recognition methods for the identification tests (Wang et al. 2012). The proposed methodology (Hassan et al. 2018) involves reduced computational complexity and aims at pest detection not only in a greenhouse environment, but also in a farm environment as well. The whitefly, a bio-aggressor which poses a threat to a multitude of crops, was chosen as the pest of interest. (Dogan et. al. 2016) developed a Microbial-based Production System (MPS) for greenhouse-grown peppers. In this work, only microbial-based products were used to suppress and control invertebrate pests and diseases. A lot of research has been carried out on crops to control pests and diseases by biological means instead of pesticides. Now, a strong demand exists for non-chemical control methods for pests or diseases. With recent advancement in image processing techniques (Haware 2018; Selvaraj et. al. 2019; Chaudhary et. al 2020), it is possible to develop an automated system for pest identification in crops. In this research paper, the main focus is on early pest detection. An image acquisition system records/captures a video of plant leaves of the crop and converts them into images or frames. 60% of the images are used for training and 40% of the images are used for testing. The plant images have been acquired using a digital camera from a greenhouse and the images are processed using artificial intelligence techniques to interpret the image content. The results of pest recognition system shall be shared with farmers for subsequent actions. The real time implementation of this work with thousands of images was carried out in a greenhouse.

MATERIAL AND METHODS

The pest recognition system for a greenhouse consists of a computer with image processing algorithms and an IP camera. The techniques used to find the different types of pests are the k-means clustering algorithm, an Artificial Neural Network (ANN) and a Support Vector Machine (SVM). The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. K-means clustering is a fast, robust, and simple algorithm that gives reliable results when data sets are distinct or well separated from each other in a linear fashion. It is best used when the number of cluster centres is specified due to being a well-defined type. An ANN is a computational model based on the structure and functions of biological neural networks. ANNs are considered non-linear statistical data modelling tools

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where the complex relationships between inputs and outputs are modelled or patterns are found. The Back Propagation Algorithm has been used in this work. This algorithm searches for weight values that minimise the total error of the network over a set of training examples. A Support Vector Machine is a powerful tool for binary classification, capable of generating very fast classifier functions following a training period. The basic idea of a binary support vector machine is to find a hyper plane which separates the d-dimensional data perfectly into its two classes. The reported system consists of various stages, including a collection of images of pests from the greenhouse, pre-processing, image segmentation, edge detection, feature extraction and classification. Figure 1 shows the methodology used to detect the pests. The images are captured by using a pan tilt zoom camera maintaining equal illumination to the object as shown in Figure 2. The pan tilt zoom camera is interfaced with the system and an android mobile which will take the image captured by the camera as an input.

This reported work was implemented on the greenhouse crops, namely capsicum and cucumber, as shown in Figure 3. The captured images of unaffected leaves, affected leaves and different types of pests that affect the crops under study are given in Figures 4–6, respectively. Image pre-processing is a process that cleans up noise and allows for the selective highlighting of information. Image segmentation is the process where the image is partitioned into multiple segments. A segment is basically a set of pixels, and is also called a super pixel. It aims

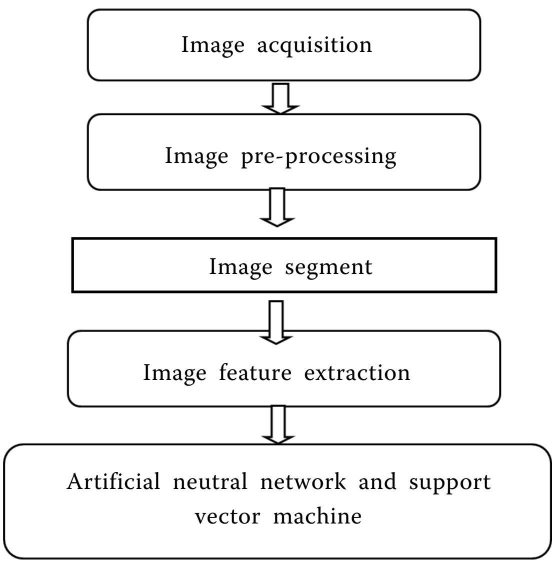

Figure 1. Methodology for the pest recognition

to simplify and changes the representation of an image such that it becomes more meaningful and easier to analyse. The result of the image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as the colour, intensity, or texture. In this work, two segmentation methods, namely global thresholding and k- means clustering, are used.

Global thresholding is the simplest image segmentation. A brightness threshold may be selected to segment the image into an object and the background. *T* is a predefined threshold. Its value can be determined by an interactive fashion or it can

Figure 2. Installed IP Camera

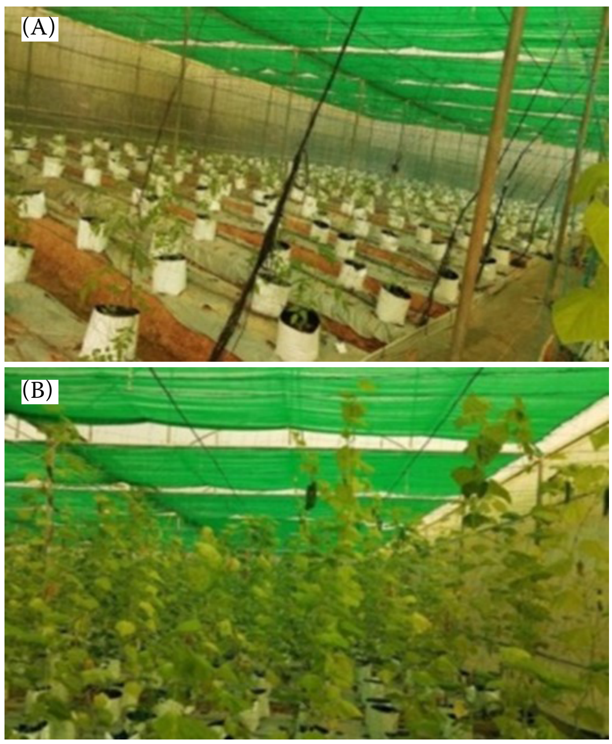

Figure 3. Greenhouse crops
(A) capsicum; (B) cucumber

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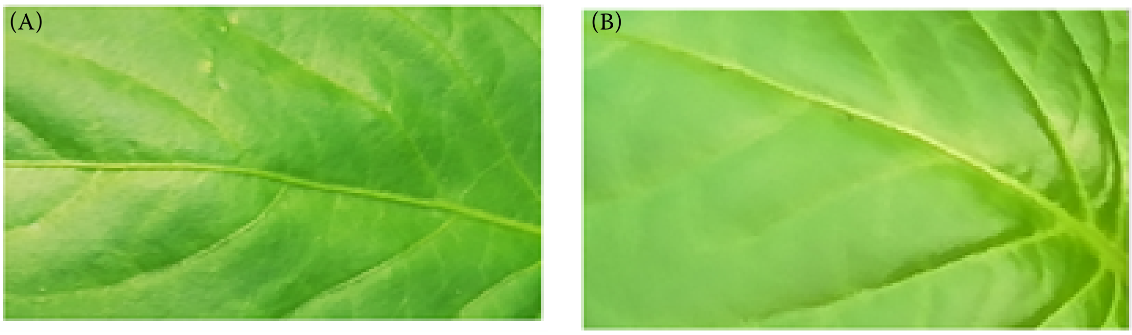

Figure 4. Unaffected leaves
(A) leaf 1; (B) leaf 2

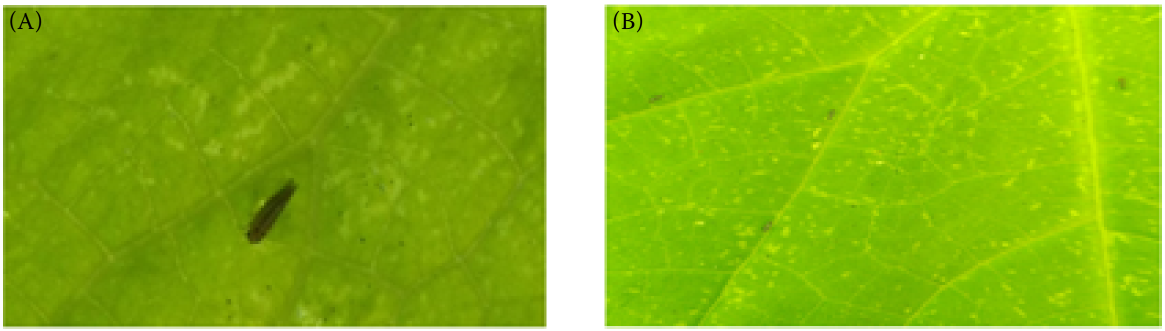

Figure 5. Pest affected leaves
(A) leaf 1; (B) leaf 2

be the result of an automatic threshold selection method. All the pixels having an intensity threshold value are set to 0; the rest are set to 1. The K-means clustering algorithm is an unsupervised algorithm and it is used to segment the interested area from the background. K-means clustering is a method of vector quantisation. A cluster is a collection of objects which are similar between each other and are dissimilar to the objects belonging to other clusters. In this work, the data were divided into

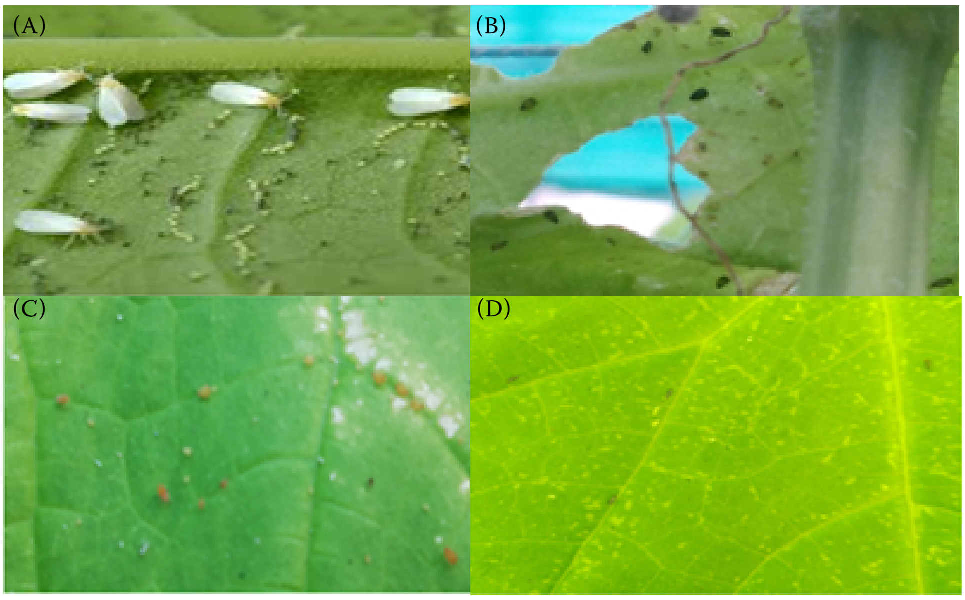

Figure 6. Types of pests
(A) white flies; (B) mites; (C) aphids; (D) thrips

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3 clusters. This algorithm works iteratively to assign each data point to one of the K groups based on the features that are provided.

The detection of edges allows us to store structural information of the objects present in an image in a very small storage area. It also reduces the communication overhead. It identifies all the lines that form outline of the objects present in the image. The difference in the intensity or brightness levels is detected by detection methods.

Feature extraction. Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. The features like entropy, mean, standard deviation, contrast, energy, correlation, variance, smoothness, and kurtosis are extracted from the segmented images. The list of features of the pest affected leaves, unaffected leaves and leaves affected with white flies, aphids, mites and thrips are tabulated in Tables 1–3, respectively.

In this paper, a binary SVM classifier and ANN classifier are used to classify the affected and unaffected leaf images and a multi SVM classifier is used to classify the types of pests present in the leaf images. Based on this, the data are provided to train the classifiers. The input images are given to the classifiers, as the classifiers are trained with the data collected from a real time greenhouse. The classifiers generate the output based on the comparison with the parameters.

Artificial neutral network classifier. ANNs are a family of models inspired by biological neural networks which are used to estimate or approximate functions that can depend on a large number of inputs that are generally unknown. It is a back propagation network with a default sigmoid transfer function. The entire data set is divided into two subsets.

Table 1. List of the extracted features for the pest affected leaves

Features leaf samples	Mean	Median	Standard deviation	Variance	Kurtosis	Skewness
1.	133.82	126	3.040	9019.07	–1.855	7.248
2.	133.48	130.66	7.318	184 034.51	1.479	270.454
3.	151.19	153.22	8.654	344 377.17	–5.766	384.082
4.	133.83	126.55	4.102	27 574.64	–12.755	4.228
5.	135.91	128.86	3.839	24 144.59	–1.121	7.5092
6.	135.04	129.97	3.266	13 706.73	–1.454	3.0156
7.	139.66	137.33	5.507	45 041.67	–1.075	2.7238
8.	105.87	102.22	8.085	172 101.56	–0.517	5.5188
9.	123.26	132.66	8.248	364 806.81	1.415	54.866
10.	168.49	164.66	7.649	146 134.84	0.032	133.457
11.	108.37	104.67	8.432	208 052.68	–3.31443	5.4036

Table 2. List of the extracted features for the unaffected leaves

Features leaf samples	Mean	Median	Standard deviation	Variance	Kurtosis	Skewness
1.	134.439	135.111	3.2618	10 387.98	–0.966	4.235
2.	138.547	136.222	1.0134	162.7764	–10.575	11.516
3.	138.114	137.889	2.2047	3 261.572	–1.572	3.282
4.	138.885	137.885	2.2099	2 720.588	–1.644	2.795
5.	135.354	127.446	2.9790	11 124.97	–0.965	6.832
6.	130.867	128.611	1.7376	1 922.617	–1.933	3.925
7.	144.886	145.8333	0.9402	228.2266	–6.571	4.952
8.	138.272	136.277	0.8704	136.1855	–11.246	9.657
9.	152.259	149.138	2.7684	27 992.91	–2.131	94.118
10.	167.611	169.889	5.1206	7 484.778	–0.268	4.033
11.	167.282	170.916	5.1501	24 605.01	–0.688	11.485

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Table 3. Extracted features for the leaves affected with white flies, aphids, mites and thrips

Features leaf samples	Mean	Standard deviation	Entropy	RMS	Variance	Smoothness
1.	24.4778	62.1920	1.26187	5.35647	2 000.445	1.367
2.	23.4629	62.1289	3.1829	5.0606	1 987.24	0.976
3.	28.3546	65.2891	2.3548	6.3452	3 546.46	0.8088
4.	21.3547	60.1278	1.38626	7.2645	3 267.289	1
5.	32.3218	59.2809	1.3739	5.3682	2 200.369	1.356
6.	35.1248	59.3728	1.2345	8.3647	199.087	0.836
7.	24.2356	50.2668	2.1567	8.9908	1 987.097	0.8689
8.	28.9725	61.2879	1.0098	8.3789	2 097.907	1.982
9.	29.3546	62.1578	1.0096	9.0076	2 356.976	0.898
10.	32.3577	63.0987	2.0657	8.2567	2 416.279	0.909
11.	31.2678	62.2890	2.0768	7.8989	2 017.009	1.2343

Features leaf samples	Kurtosis	Skewness	Contrast	Correlation	Energy	Homogeneity
1.	8.4867	2.546	0.3878	0.9512	0.4567	0.843
2.	9.3367	2.134	0.2637	0.8746	0.5372	0.877
3.	7.278	3.468	0.2732	0.9864	0.6399	0.860
4.	10.278	2.098	0.2456	0.5643	0.4278	0.867
5.	8.098	2.365	0.4801	0.9874	0.2678	0.958
6.	8.648	3.7289	0.3677	0.8764	0.1234	0.842
7.	3.098	3.798	0.5678	0.9856	0.5467	0.847
8.	3.879	4.092	0.6789	0.699	0.53218	0.117
9.	5.989	3.0864	0.5647	0.9854	0.56473	0.123
10.	6.0977	3.0954	0.8989	0.5656	0.5878	0.980
11.	7.2879	2.234	0.3434	0.5678	0.5379	0.156

The training set is the first subset that is used for calculating the radiant and updating the network biases and weights. The validation set is the second subset. The error on the validation set is monitored during the training process. The validation error normally reduces during the initial face of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set begins to increase.

The number of hidden layers also has to be fixed to gain efficiency in the classification. Based on the comparison of the output and target, the network is adjusted until the network output matches the target. The ANN architecture is shown in Figure 7. ANN consists of an input layer, one hidden layer with five neurons and an output layer. The six inputs are the extracted features and the output is the normal leaf of the pest affected leaf. It is clear from Figure 8 that the error tends to decrease after more epochs of training, but might start to increase on the validation data set as the network starts to over fit the training data. The testing state almost matches the validation state with a negligible error. From the obtained training plot, it is clear that the gradient decreases as the learning rate increases.

Binary SVM calssifier. SVM is popularly used in many pattern recognition problems including texture classification. This is conducted by maximising the margin from the hyper plane. The samples closest to the margin that were selected to determine the hyper plane are known as support vectors. SVMs give good performance in many real time applications. Sequential Minimum Optimisation (SMO) is the SVM training algorithm used in this research. SMO solves the Lagrange multipliers analytically. The output of SVM is computed from the Lagrange multipliers (Equation 1):

$$u = \sum_{j=1}^{N} y_j \alpha_j \; k(\bar{x}_{j,} \; \bar{x}) - d \qquad (1)$$

where: k is a kernel function that measures the similar-

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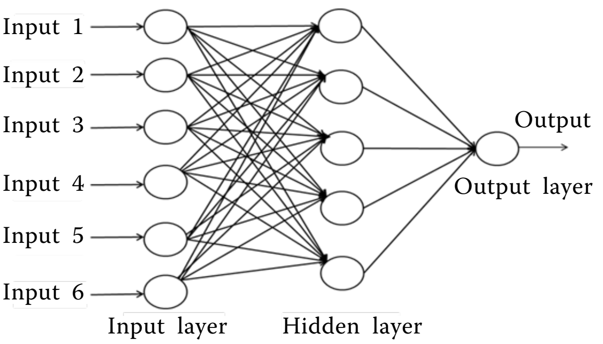

Figure 7. Architecture of Artificial Neural Network (ANN)

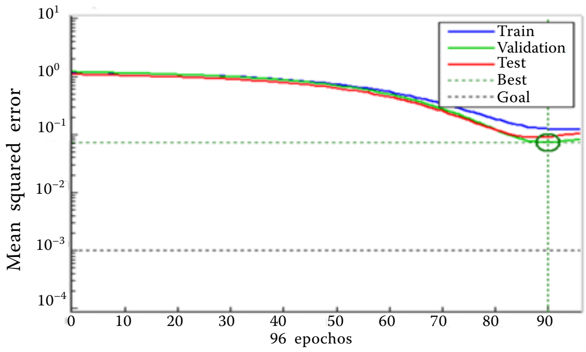

Figure 8. Performance plot

ity of $\bar{x}$ and $\bar{x}_j$. The Lagrange multipliers are computed through a quadratic programme. The dual objective function Ψ is given by

$$\Psi\left(\bar{\alpha}\right)=\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j k\left(\bar{x}_i,\bar{x}_j\right)\alpha_i\alpha_j-\sum_{i=1}^{N}\alpha_i \quad 0\le\alpha_i\le C,\forall_i$$

$$\sum_{i=1}^{N}y_i\alpha_i=0 \tag{2}$$

where: N – the number of training samples. C is the trade-off between the training error and generalisation factor. The Karush-Kuhn-Tucker (KKT) conditions for Equation (2) are:

$\alpha_i = 0 \Leftrightarrow y_i u_i \ge 1$, $0 < \alpha_i < C \Leftrightarrow y_i u_i = 1$ and
$\alpha_i = C \Leftrightarrow y_i u_i \le 1$

where: u_i – the output of the SVM for the i^{th} training.

The SMO algorithm first computes the second Lagrange multiplier α_2.

If the target $y_1 \# y_2$, then

$$L = \max(0, \alpha_2 - \alpha_1),\ H = \min(C, C + \alpha_2 + \alpha_1)$$

If y_1 = target y_2, then

$$L = \max(0, \alpha_2 + \alpha_1 - C),\ H = \min(C, \alpha_2 + K_1)$$

The second derivative of the objective function can be written as (Equation 3):

$$\eta = K(\bar{x}_1,\bar{x}_1)+K(\bar{x}_2,\bar{x}_2)-2K(\bar{x}_1,\bar{x}_2) \tag{3}$$

Under normal conditions, the objective function will be positive and η will be greater than zero. Now, the SMO computes the minimum along the direction of the constraint.

$$\alpha_2^{\text{new}}=\alpha_2+\frac{y_2\ (E_1-E_2)}{\eta}$$

Where $E_i = u_i - y_i$ is the i^{th} sample training error.

$$\alpha_2^{\text{new, clipped}}=\begin{cases} H \text{ if } \alpha_2^{\text{new}}\ge H \\ \alpha_2^{\text{new}} \text{ if } L<\alpha_2^{\text{new}}<H \\ L \text{ if } \alpha_2^{\text{new}}\le L \end{cases} \tag{4}$$

Consider $S = y_1 y_2$ and α_1 is computed from (Equation 4)

$$\alpha_1^{\text{new}} = \alpha_1 + s(\alpha_2 - \alpha_2^{\text{new, clipped}})$$

The SMO algorithm will be suitable even when η is negative, in such a case ψ should be evaluated at the end of each line segment given in Equations (5) to (9)

$$f_1 = y_1\left(E_1+b\right)-\alpha_1 K(\bar{x}_1,\bar{x}_1)-s\alpha_2 K(\bar{x}_1,\bar{x}_2) \tag{5}$$

$$f_2 = y_2\left(E_2+b\right)-s\alpha_1 K(\bar{x}_1,\bar{x}_2)-\alpha_2 K(\bar{x}_2,\bar{x}_2) \tag{6}$$

$$L_1 = \alpha_1 + s(\alpha_2 - L) \tag{7}$$

$$H_1 = \alpha_1 + s(\alpha_2 - H) \tag{8}$$

$$\Psi_L = L_1 f_1 + L f_2 + \frac{1}{2}L_1^2 K(\bar{x}_1,\bar{x}_1)+\frac{1}{2}L^2 K(\bar{x}_2,\bar{x}_2)+ + SLL_1 K(\bar{x}_1,\bar{x}_2) \tag{9}$$

$$\Psi_H = H_1 f_1 + H f_2 + H_1^2 K(\bar{x}_1,\bar{x}_1)+\frac{1}{2}H^2 K(\bar{x}_2,\bar{x}_2)+ + SHH_1 K(\bar{x}_1,\bar{x}_2) \tag{10}$$

The threshold ‘d’ is computed after every step, so that the KKT conditions are satisfied. The performance of the SVM can be improved by tuning the parameters such as the kernel, gamma and penalty parameter. The results of the binary SVM for the pest affected leaf1, leaf2 and normal leaf are shown in Figure 9.

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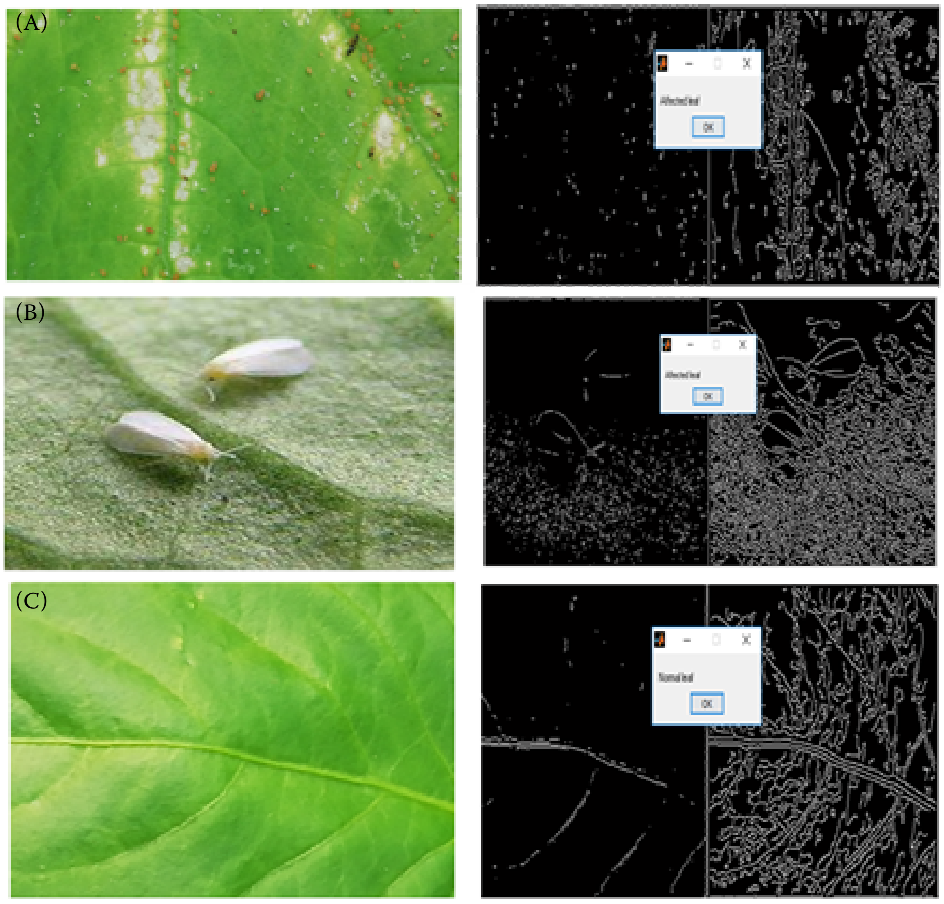

Figure 9. Binary Support Vector Machine (SVM) results
(A) pest affected leaf 1; (B) pest affected leaf 2; (C) unaffected/normal leaf

The accuracy of the classifications is compared in Table 4. The accuracy of the binary SVM classifier is 88% when compared to the 84% accuracy of the SVM classification of Butterfly and Grasshopper (Hassan et. al. 2014) based on the colour and the shape features. The accuracy of the classification can be further improved by using principal component analysis as feature selection method.

Multi SVM classifier. If the leaf is found to be infected, then the next step is to find out the type of pest. The four categories of pests that are considered in this work are white flies, aphids, thrips and mites.

Table 4. Accuracy of the pest identification using Support Vector Machine (SVM) and Artificial Neural Network (ANN)

S. No	Methods	Accuracy
1	ANN	85.12%
2	Binary - SVM	88.81%
3	Multi - SVM	91.78

For the above pest classification, a multi-SVM classifier has been used. Multiclass classification is applicable and basically built up by various two class SVMs to solve the problem. The classifier evaluates such as the output value higher than the threshold area is recorded as true and lower than the threshold area is recorded as false.

The multi-SVM generates the output as the type of pest present in the leaf as shown in Figure 10. The overall efficiency of the multi-SVM is 91.78%. The accuracy of the classification can be further improved by a Convolutional Neural Network (CNN) with a higher number of features and a feature selection technique like Principal Component Analysis (PCA).

CONCLUSION

The main objective of this work is to detect pests as early as possible and reduce the use of pesticides.

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Classification result Apids | Affected region (%) 15.01878 | Accuracy (%) Apid 96.7744

Figure 10. Multi-SVM result

Image processing techniques play a vital role in the detection of pests. The major techniques used here are K-means clustering, a Binary Support Vector Machine classifier, an ANN classifier and a multi-SVM. A pan tilt zoom camera has been used to interface with the system. The images captured using this camera are given as the input to the classifiers (ANN and SVM). The classification accuracy of the Binary SVM is higher than ANN. The accuracy of the ANN can be further improved by a CNN with a large dataset. The computation efficiency of the multi-SVM tends to perform with an accuracy of 91.78%. The system proved reliable for the rapid detection of pests. The result presented in this paper is promising, but several improvements on both the materials and methods will be carried out to reach the requirements of a fully automated pest detection and identification system.

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